Final Project: Effects on NYC Public Transportation

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This project will study what effects changes on NYC Public Transportation. There are several considerations, including the introduction of Uber, population, and weather. It is easy to believe that there are obvious patterns (more Uber, less public transportation; more population, less usage; bad weather, less usage), but I am interested in exploring this further.

The key element of the project is the use of datasets from the New York Metropolitan Transportation Council (https://www.nymtc.org/DATA-AND-MODELING//Transportation-Data-and-Statistics/Publications/Travel-Patterns). This dataset provides usage data over many years. I will be using ridership totals across the following categories: MTA Rail, Buses, Port Authority, and NJ Transit. I will also be using Q1-4 from the years of 2008-2017.

I also use population data from weather data from the U.S. Census, and weather data from: https://raw.githubusercontent.com/toddwschneider/nyc-taxi-data/master/data/central_park_weather.csv (https://raw.githubusercontent.com/toddwschneider/nyc-taxi-data/master/data/central_park_weather.csv)

Data Packages

This project will use a variety of packages to manipulate data and produce insightful graphics. A brief description of how each package will be used is given.

In [393]:
```
import pandas as pd #main package for dataset and visualizations
import matplotlib.pyplot as plt #visualization package
import numpy as np #for numerical functions
import requests #extracting data from APIs

from census import Census #this is the most up-to-date U.S. census data
from us import states
my_api_key = '34e40301bda77077e24c859c6c6c0b721ad73fc7'
c = Census(my_api_key)

import seaborn as sns #for regression plot visualization
import matplotlib.ticker as mtick #for axes unit formatting on plots
```

In [493]:
```
pd.options.mode.chained_assignment = None
```

Read in NYC Transit Data

In [97]:
```
file = "https://raw.githubusercontent.com/jenniferrkim/public-transport-data-bootcamp-final-project/master/NYCTransitData.csv"
transit_data_raw = pd.read_csv(file)
```

In [98]:
```
transit_data_raw.head()
```

Out[98]:

	Bus and Rail RIDERSHIP	Average Q1 2008	Average Q2 2008	Average Q3 2008	Average Q4 2008	Average Q1 2009	Average Q2 2009	Avera Q3 2(
0	NEW YORK TRANSIT RAIL SYSTEM	NaN	NaN	NaN	NaN	NaN	NaN	N
1	MTA/NYC Transit Subway	5138104.00	5327590.33	5193139.00	5239010.67	5057695.33	5140976.67	4939108
2	MTA/Staten Island Railway	16192.67	16014.00	14816.67	15904.00	15236.00	14870.00	13520
3	MTA/Metro-North Railroad	276133.67	289732.67	291616.67	290999.33	269599.67	277356.33	273540
4	MTA/Long Island Rail Road	298012.00	312185.33	320050.33	307700.33	281407.00	285942.33	288358

5 rows × 41 columns

Contextualize and Clean Data

In [494]:
```
#drop rows that are just category titles
transit_data = transit_data_raw.dropna(axis = 0)

#simplify titles of columns, as we know they are averages, and they currently
 have a lot of white space
transit_data.columns = ["Transport Type (Specific)",
                        "2008 Q1", "2008 Q2", "2008 Q3", "2008 Q4",
                        "2009 Q1", "2009 Q2", "2009 Q3", "2009 Q4",
                        "2010 Q1", "2010 Q2", "2010 Q3", "2010 Q4",
                        "2011 Q1", "2011 Q2", "2011 Q3", "2011 Q4",
                        "2012 Q1", "2012 Q2", "2012 Q3", "2012 Q4",
                        "2013 Q1", "2013 Q2", "2013 Q3", "2013 Q4",
                        "2014 Q1", "2014 Q2", "2014 Q3", "2014 Q4",
                        "2015 Q1", "2015 Q2", "2015 Q3", "2015 Q4",
                        "2016 Q1", "2016 Q2", "2016 Q3", "2016 Q4",
                        "2017 Q1", "2017 Q2", "2017 Q3", "2017 Q4"]

#create columns for broad transport type classification (no specific pattern i
n names so done manually)
transit_data["Transport Type (Broad)"] = ["MTA Rail", "MTA Rail", "MTA Rail",
"MTA Rail", "MTA Rail",
                                          "NYC Buses", "NYC Buses", "NYC Buses"
, "NYC Buses",
                                          "PATH", "PATH", "PATH",
                                          "NJ Rail", "NJ Rail", "NJ Rail", "NJ
 Rail", "NJ Rail",
                                          "Airport Rail", "Airport Rail", "Airp
ort Rail",
                                          "Suburban Buses", "Suburban Buses",
"Suburban Buses", "Suburban Buses", "Suburban Buses", "Suburban Buses", "Subur
ban Buses", "Suburban Buses", "Suburban Buses", "Suburban Buses",
                                          "Grand Total"]

#move the Broad transport type category columns to the front
cols = transit_data.columns.tolist()
cols = cols[-1:] + cols[:-1] #move last col to first position
transit_data = transit_data[cols] #rearrange columns according to list
```

Ridership Over the Years (2008 - 2017) by Broad Transportation Type

We first want to see how ridership has changed over the years in NYC by each broad transportation type. The types are: MTA Rail, NYC Buses, PATH, NJ Rail, Airport Rail, and Suburban Buses. To see how each has changed, we need to first categorize the numbers into each transportation type and combine the numbers for the Quarter into their respective years.

In [196]:
```
typebyyear = transit_data #create a new dataframe
typebyyear.set_index(["Transport Type (Broad)"], inplace = True) #set index to
the transport type, which we will later group by
```

In [220]:

```
#want to create total for each quarter for each broad transport type category
typebyyear["2008"] = transit_data.iloc[:, 1:5].sum(axis = 1)
typebyyear["2009"] = transit_data.iloc[:, 5:9].sum(axis = 1)
typebyyear["2010"] = transit_data.iloc[:, 9:13].sum(axis = 1)
typebyyear["2011"] = transit_data.iloc[:, 13:17].sum(axis = 1)
typebyyear["2012"] = transit_data.iloc[:, 17:21].sum(axis = 1)
typebyyear["2013"] = transit_data.iloc[:, 21:25].sum(axis = 1)
typebyyear["2014"] = transit_data.iloc[:, 25:29].sum(axis = 1)
typebyyear["2015"] = transit_data.iloc[:, 29:33].sum(axis = 1)
typebyyear["2016"] = transit_data.iloc[:, 33:37].sum(axis = 1)
typebyyear["2017"] = transit_data.iloc[:, 37:41].sum(axis = 1)

#grab only the new year columns
typebyyear2 = typebyyear[typebyyear.columns[41:]]

typebyyear2.head()
```

Out[220]:

	2008	2009	2010	2011	2012	2013	
Transport Type (Broad)							
MTA Rail	20897844.00	20332815.38	20608661.60	21072461.89	21529235.67	21865879.34	22389
MTA Rail	62927.34	59039.71	61697.46	63893.22	64056.00	60243.33	61
MTA Rail	1148482.34	1098851.39	1113958.34	1125794.34	1125328.33	1136708.33	1157
MTA Rail	1237947.99	1141494.94	1129432.33	1132992.01	1140329.33	1162107.66	1193
MTA Rail	23347201.66	22632201.41	22913749.73	23395141.44	23858949.34	24224938.67	24802

Now that we have categorized all the Quarters into their respective years, we need to sum up each minute transportation option into their respective, more general category. To do this, we will use groupby.

In [339]:
```
typebyyear2 = typebyyear2.groupby(["Transport Type (Broad)"]).sum() #add up ri
dership for each category

typebyyeardrop = typebyyear2.drop("Grand Total", axis = 0)

typebyyeardrop
```

Out[339]:

Transport Type (Broad)	2008	2009	2010	2011	2012	2013	
Airport Rail	182624.90	139186.01	156735.70	167062.04	171100.88	183670.01	189
MTA Rail	46694403.33	45264402.83	45827499.46	46790282.90	47717898.67	48449877.33	49604
NJ Rail	2842500.00	2706600.00	2663400.00	2854600.00	2856700.00	2946300.00	3082
NYC Buses	22233213.83	21702591.23	20962959.21	20197426.00	20507348.34	20615538.44	20254
PATH	2021611.99	1948091.36	1975068.02	2047458.65	1928940.66	1955451.35	1998
Suburban Buses	6652844.70	6420271.51	6371018.48	6316516.29	6430494.90	6434628.75	6392

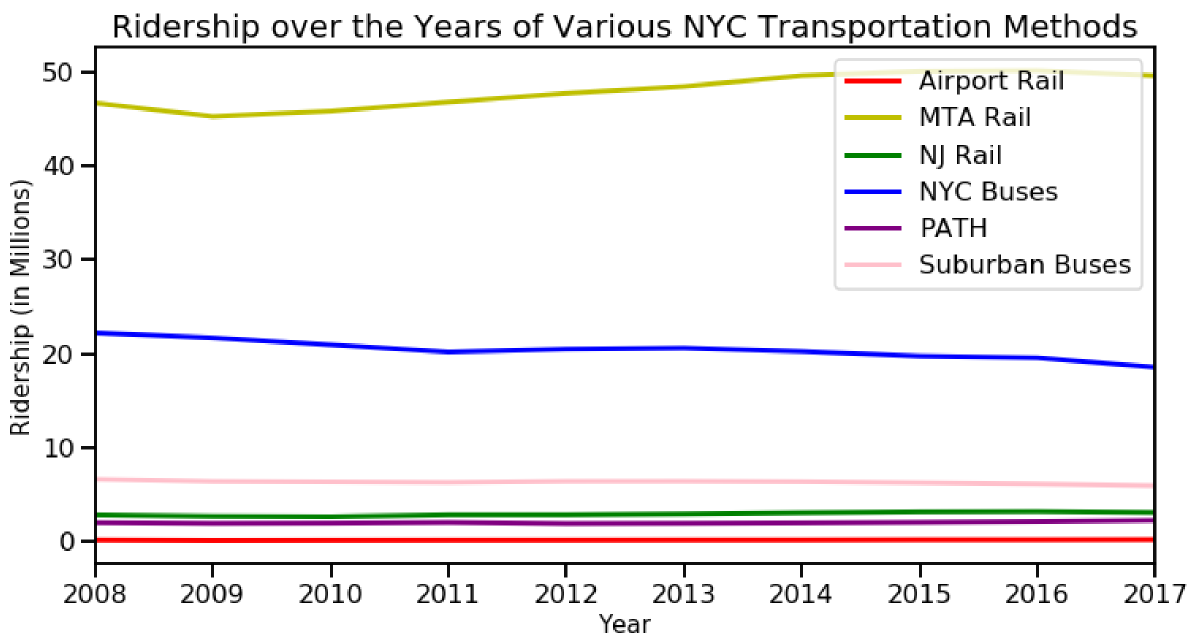
In [292]:
```
typebyyear3 = typebyyeardrop.transpose()

typebyyear3.index = pd.to_numeric(typebyyear3.index) #years are strings, need
 to convert to int

typebyyear3.head()
```

Out[292]:

Transport Type (Broad)	Airport Rail	MTA Rail	NJ Rail	NYC Buses	PATH	Suburban Buses
2008	182624.90	46694403.33	2842500.0	22233213.83	2021611.99	6652844.70
2009	139186.01	45264402.83	2706600.0	21702591.23	1948091.36	6420271.51
2010	156735.70	45827499.46	2663400.0	20962959.21	1975068.02	6371018.48
2011	167062.04	46790282.90	2854600.0	20197426.00	2047458.65	6316516.29
2012	171100.88	47717898.67	2856700.0	20507348.34	1928940.66	6430494.90

Now plot!

In [313]:
```
fig, ax1 = plt.subplots(figsize = (12, 6))

ax1.plot(typebyyear3.index, typebyyear3["Airport Rail"] / 1000000, color = 'r'
, linewidth = 3, label = "Airport Rail")
ax1.plot(typebyyear3.index, typebyyear3["MTA Rail"] / 1000000, color = 'y', li
newidth = 3, label = "MTA Rail")
ax1.plot(typebyyear3.index, typebyyear3["NJ Rail"] / 1000000, color = 'g', lin
ewidth = 3, label = "NJ Rail")
ax1.plot(typebyyear3.index, typebyyear3["NYC Buses"] / 1000000, color = 'b', l
inewidth = 3, label = "NYC Buses")
ax1.plot(typebyyear3.index, typebyyear3["PATH"] / 1000000, color = 'purple', l
inewidth = 3, label = "PATH")
ax1.plot(typebyyear3.index, typebyyear3["Suburban Buses"] / 1000000, color =
'pink', linewidth = 3, label = "Suburban Buses")

ax1.set_title("Ridership over the Years of Various NYC Transportation Methods"
, fontsize = 20)
ax1.title.set_position([.5, 1])

ax1.set_xlabel("Year", fontsize = 15)
ax1.set_ylabel("Ridership (in Millions)", fontsize = 15)

ax1.set_xlim(2008, 2017)

ax1.legend(loc=1)

plt.show()
```

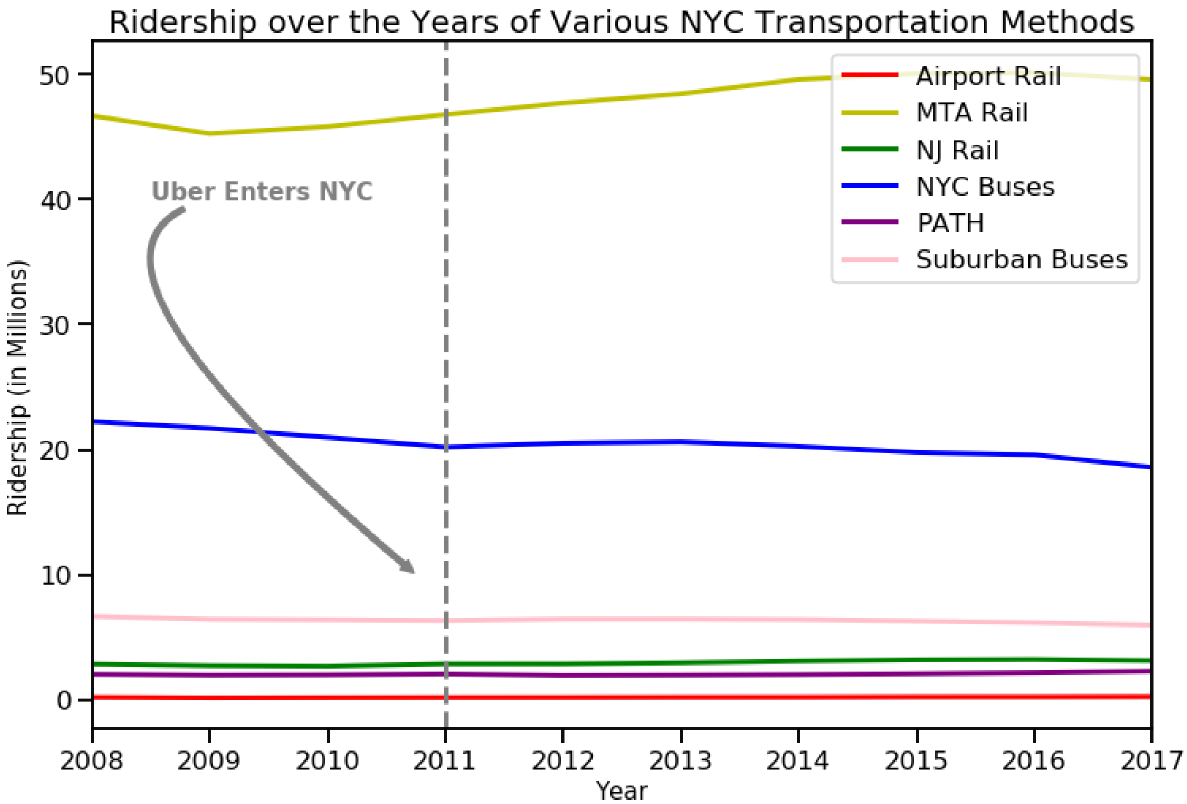


Here we see that the NYC Buses and MTA Rail have the greatest use compared to the other four transportation methods.

Effect of Uber on Public Transportation

Now, I am curious as to what effect there was when Uber entered NYC. First, I will show on the graph the time when Uber entered the city.

In [335]:
```
fig, ax1 = plt.subplots(figsize = (12, 8))

ax1.plot(typebyyear3.index, typebyyear3["Airport Rail"] / 1000000, color = 'r'
, linewidth = 3, label = "Airport Rail")
ax1.plot(typebyyear3.index, typebyyear3["MTA Rail"] / 1000000, color = 'y', li
newidth = 3, label = "MTA Rail")
ax1.plot(typebyyear3.index, typebyyear3["NJ Rail"] / 1000000, color = 'g', lin
ewidth = 3, label = "NJ Rail")
ax1.plot(typebyyear3.index, typebyyear3["NYC Buses"] / 1000000, color = 'b', l
inewidth = 3, label = "NYC Buses")
ax1.plot(typebyyear3.index, typebyyear3["PATH"] / 1000000, color = 'purple', l
inewidth = 3, label = "PATH")
ax1.plot(typebyyear3.index, typebyyear3["Suburban Buses"] / 1000000, color =
'pink', linewidth = 3, label = "Suburban Buses")

ax1.set_title("Ridership over the Years of Various NYC Transportation Methods"
, fontsize = 20)
ax1.title.set_position([.5, 1])

ax1.set_xlabel("Year", fontsize = 15)
ax1.set_ylabel("Ridership (in Millions)", fontsize = 15)

ax1.set_xlim(2008, 2017)

ax1.legend(loc=1)

#adding line to indicate when Uber entered the space
plt.axvline(x = 2011., color = "gray", linewidth = 3.0, linestyle = "--")

ax1.annotate("Uber Enters NYC",
             xy = (2010.75, 10),
             xytext = (2008.5, 40),
             fontsize = 15,
             fontweight = "bold",
             color = "gray",
             arrowprops = {
                 "arrowstyle": "simple",
                 "connectionstyle": "angle3, angleA = 3, angleB = 140",
                 "color": "gray"})

plt.show()
```



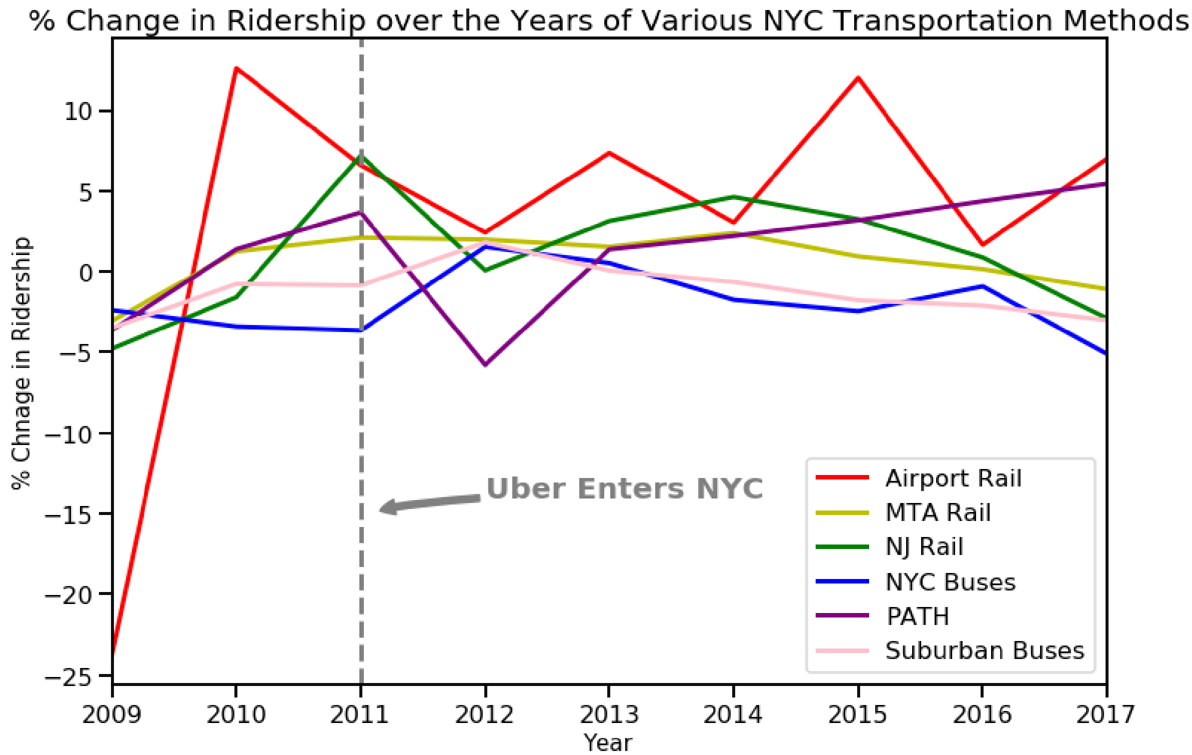
It seems as though there is no obvious change to the eye just by this graph. To dig deeper, we can see what the % change year over year is.

In [377]:
```
#finding % change year over year
typebyyoy = typebyyeardrop

i=0
df = pd.DataFrame()
while i < 9:
    df[i] = ((typebyyoy.iloc[:, i+1] - typebyyoy.iloc[:, i]) / typebyyoy.iloc
[:, i])*100
    df.append(df[i])
    i = i +1

typebyyoy = df[0:9]

#rename columns
typebyyoy.columns = [2009, 2010, 2011,
                     2012, 2013, 2014,
                     2015, 2016, 2017]

typebyyoy
```

Out[377]:

	2009	2010	2011	2012	2013	2014	2015	2016
Transport Type (Broad)								
Airport Rail	-23.785853	12.608803	6.588378	2.417569	7.346035	3.039957	11.994452	1.654467
MTA Rail	-3.062467	1.244016	2.100886	1.982497	1.533971	2.383366	0.939054	0.152384
NJ Rail	-4.781003	-1.596098	7.178794	0.073565	3.136486	4.619353	3.244225	0.873555
NYC Buses	-2.386621	-3.408036	-3.651838	1.534465	0.527567	-1.748917	-2.453240	-0.917869
PATH	-3.636733	1.384774	3.665222	-5.788541	1.374365	2.201230	3.182661	4.360795
Suburban Buses	-3.495846	-0.767149	-0.855471	1.804454	0.064285	-0.649855	-1.778737	-2.104117

In [392]:
```
typebyyoyT = typebyyoy.transpose()
fig, ax1 = plt.subplots(figsize = (12, 8))

ax1.plot(typebyyoyT.index, typebyyoyT["Airport Rail"], color = 'r', linewidth
= 3, label = "Airport Rail")
ax1.plot(typebyyoyT.index, typebyyoyT["MTA Rail"], color = 'y', linewidth = 3,
label = "MTA Rail")
ax1.plot(typebyyoyT.index, typebyyoyT["NJ Rail"], color = 'g', linewidth = 3,
label = "NJ Rail")
ax1.plot(typebyyoyT.index, typebyyoyT["NYC Buses"], color = 'b', linewidth = 3
, label = "NYC Buses")
ax1.plot(typebyyoyT.index, typebyyoyT["PATH"], color = 'purple', linewidth = 3
, label = "PATH")
ax1.plot(typebyyoyT.index, typebyyoyT["Suburban Buses"], color = 'pink', linew
idth = 3, label = "Suburban Buses")

ax1.set_title("% Change in Ridership over the Years of Various NYC Transportat
ion Methods", fontsize = 20)
ax1.title.set_position([.5, 1])

ax1.set_xlabel("Year", fontsize = 15)
ax1.set_ylabel("% Chnage in Ridership", fontsize = 15)

ax1.set_xlim(2009, 2017)

#adding line to indicate when Uber entered the space
plt.axvline(x = 2011., color = "gray", linewidth = 3.0, linestyle = "--")

ax1.annotate("Uber Enters NYC",
             xy = (2011.15, -15),
             xytext = (2012, -14),
             fontsize = 20,
             fontweight = "bold",
             color = "gray",
             arrowprops = {
                 "arrowstyle": "simple",
                 "connectionstyle": "angle3, angleA = 3, angleB = 140",
                 "color": "gray"})

ax1.legend()

plt.show()
```



It seems that immediately after, most transportation use went down, except for Suburban buses and NYC buses. Perhaps this is because those who ride buses are usually those who do not have the means to pay for a private car.

Overall, it looks as though the Airport Rail is the most volatile, while others, especially the NYC buses, MTA rail, and suburban buses usage stay pretty constant.

However, we cannot draw any real conclusions from this and still do not know if the changes are significant.

Ridership per Person: Using U.S. Census Population Data

To take away effects of people moving in and out of the city, we can take into account changes in population. Recently, there has been a decrease in population due to a migration of people outside of cities. We can see if that applies here by graphing ridership per person in Manhattan.

This data is taken from the U.S. Census.

In [477]:
```
#Using the U.S. Census to grab New York population data
# combine data frames for each borough in nyc
code = ("NAME", "B01001_001E")
bronx_pop_2009 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2009))
bronx_pop_2010 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2010))
bronx_pop_2011 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2011))
bronx_pop_2012 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2012))
bronx_pop_2013 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2013))
bronx_pop_2014 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2014))
bronx_pop_2015 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2015))
bronx_pop_2016 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2016))
bronx_pop_2017 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "005",
year=2017))
bronx_pop = bronx_pop_2009.append([bronx_pop_2010, bronx_pop_2011, bronx_pop_2
012, bronx_pop_2013, bronx_pop_2014, bronx_pop_2015, bronx_pop_2016, bronx_pop
_2017], ignore_index=True)
bronx_pop_total = pd.DataFrame({'Year': [2009, 2010, 2011, 2012, 2013, 2014, 2
015, 2016, 2017], "Total Population": bronx_pop["B01001_001E"]})

brooklyn_pop_2009 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2009))
brooklyn_pop_2010 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2010))
brooklyn_pop_2011 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2011))
brooklyn_pop_2012 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2012))
brooklyn_pop_2013 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2013))
brooklyn_pop_2014 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2014))
brooklyn_pop_2015 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2015))
brooklyn_pop_2016 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2016))
brooklyn_pop_2017 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "04
7", year=2017))
brooklyn_pop = brooklyn_pop_2009.append([brooklyn_pop_2010, brooklyn_pop_2011,
brooklyn_pop_2012, brooklyn_pop_2013, brooklyn_pop_2014, brooklyn_pop_2015, br
ooklyn_pop_2016, brooklyn_pop_2017], ignore_index=True)
brooklyn_pop_total = pd.DataFrame({'Year': [2009, 2010, 2011, 2012, 2013, 2014
, 2015, 2016, 2017], "Total Population": brooklyn_pop["B01001_001E"]})

manhattan_pop_2009 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
61", year=2009))
manhattan_pop_2010 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
61", year=2010))
manhattan_pop_2011 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
```

```
61", year=2011))
manhattan_pop_2012 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
61", year=2012))
manhattan_pop_2013 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
61", year=2013))
manhattan_pop_2014 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
61", year=2014))
manhattan_pop_2015 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
61", year=2015))
manhattan_pop_2016 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
61", year=2016))
manhattan_pop_2017 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "0
61", year=2017))
manhattan_pop = manhattan_pop_2009.append([manhattan_pop_2010, manhattan_pop_2
011, manhattan_pop_2012, manhattan_pop_2013, manhattan_pop_2014, manhattan_pop
_2015, manhattan_pop_2016, manhattan_pop_2017], ignore_index=True)
manhattan_pop_total = pd.DataFrame({'Year': [2009, 2010, 2011, 2012, 2013, 201
4, 2015, 2016, 2017], "Total Population": manhattan_pop["B01001_001E"]})

queens_pop_2009 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2009))
queens_pop_2010 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2010))
queens_pop_2011 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2011))
queens_pop_2012 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2012))
queens_pop_2013 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2013))
queens_pop_2014 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2014))
queens_pop_2015 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2015))
queens_pop_2016 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2016))
queens_pop_2017 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "081"
, year=2017))
queens_pop = queens_pop_2009.append([queens_pop_2010, queens_pop_2011, queens_
pop_2012, queens_pop_2013, queens_pop_2014, queens_pop_2015, queens_pop_2016,
queens_pop_2017], ignore_index=True)
queens_pop_total = pd.DataFrame({'Year': [2009, 2010, 2011, 2012, 2013, 2014,
2015, 2016, 2017], "Total Population": queens_pop["B01001_001E"]})

staten_pop_2009 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2009))
staten_pop_2010 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2010))
staten_pop_2011 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2011))
staten_pop_2012 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2012))
staten_pop_2013 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2013))
staten_pop_2014 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2014))
staten_pop_2015 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2015))
```

```
staten_pop_2016 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2016))
staten_pop_2017 = pd.DataFrame(c.acs5.state_county(code, states.NY.fips, "085"
, year=2017))
staten_pop = staten_pop_2009.append([staten_pop_2010, staten_pop_2011, staten_
pop_2012, staten_pop_2013, staten_pop_2014, staten_pop_2015, staten_pop_2016,
staten_pop_2017], ignore_index=True)
staten_pop_total = pd.DataFrame({'Year': [2009, 2010, 2011, 2012, 2013, 2014,
2015, 2016, 2017], "Total Population": staten_pop["B01001_001E"]})
```

In [478]:

```
# combine then group and sum all population from boroughs for total nyc pop
nyc_pop = bronx_pop_total.append([brooklyn_pop_total, manhattan_pop_total, que
ens_pop_total, staten_pop_total])
nyc_pop["Total Population"] = pd.to_numeric(nyc_pop.iloc[:, 1])
nyc_pop_total = nyc_pop.groupby(['Year']).sum()
nyc_pop_total.head()
```

Out[478]:

	Total Population
Year	
2009	8302659.0
2010	8078471.0
2011	8128980.0
2012	8199221.0
2013	8268999.0

In [479]:

```
# prepare data frame for division by removing extra column
transit_type_by_year = typebyyear2.rename_axis("Year")
transit_type_by_year_prep = transit_type_by_year.drop(['2008'], axis=1)
transit_type_by_year_prep
```

Out[479]:

	2009	2010	2011	2012	2013	2014	
Year							
Airport Rail	139186.01	156735.70	167062.04	171100.88	183670.01	189253.50	211
Grand Total	39086268.55	38978340.42	39186672.28	39806241.74	40292732.91	40761283.82	40782
MTA Rail	45264402.83	45827499.46	46790282.90	47717898.67	48449877.33	49604615.34	5007C
NJ Rail	2706600.00	2663400.00	2854600.00	2856700.00	2946300.00	3082400.00	3182
NYC Buses	21702591.23	20962959.21	20197426.00	20507348.34	20615538.44	20254989.77	19758
PATH	1948091.36	1975068.02	2047458.65	1928940.66	1955451.35	1998495.34	2062
Suburban Buses	6420271.51	6371018.48	6316516.29	6430494.90	6434628.75	6392812.98	6279

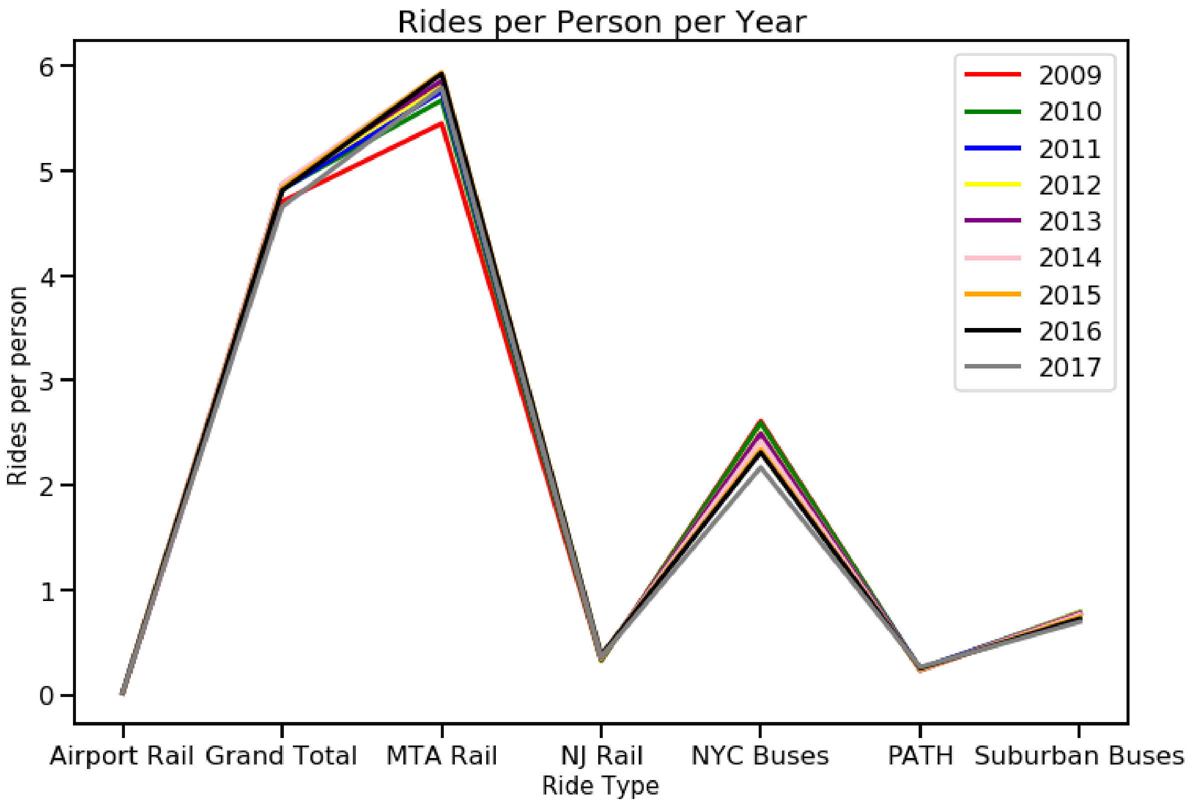
In [480]:

```
# divide ridership over nyc population
transit_type_over_population = transit_type_by_year_prep / nyc_pop_total["Tota
l Population"].values.astype(float)
transit_type_over_population = transit_type_over_population.rename(index=str,
columns={"2009": "2009 rides per person", "2010": "2010 rides per person", "20
11": "2011 rides per person", "2012": "2012 rides per person", "2013": "2013 r
ides per person", "2014": "2014 rides per person", "2015": "2015 rides per per
son", "2016": "2016 rides per person", "2017": "2017 rides per person"})
transit_type_over_population.head()
```

Out[480]:

	2009 rides per person	2010 rides per person	2011 rides per person	2012 rides per person	2013 rides per person	2014 rides per person	2015 rides per person	2016 rides per person	201 rides pe perso
Year									
Airport Rail	0.016764	0.019402	0.020551	0.020868	0.022212	0.022652	0.025152	0.025462	0.02693
Grand Total	4.707681	4.824965	4.820614	4.854881	4.872746	4.878734	4.839596	4.812604	4.65828
MTA Rail	5.451796	5.672794	5.755985	5.819809	5.859219	5.937196	5.941848	5.926136	5.79394
NJ Rail	0.325992	0.329691	0.351163	0.348411	0.356307	0.368934	0.377655	0.379368	0.36414
NYC Buses	2.613933	2.594917	2.484620	2.501134	2.493112	2.424328	2.344688	2.313498	2.17006

In [496]:
```
# graphing rides per person

fig, ax1 = plt.subplots(figsize = (12, 8))

ax1.plot(transit_type_over_population.index, transit_type_over_population["200
9 rides per person"],
         color = 'r', linewidth = 3, label = "2009")
ax1.plot(transit_type_over_population.index, transit_type_over_population["201
0 rides per person"],
         color = 'g', linewidth = 3, label = "2010")
ax1.plot(transit_type_over_population.index, transit_type_over_population["201
1 rides per person"],
         color = 'b', linewidth = 3, label = "2011")
ax1.plot(transit_type_over_population.index, transit_type_over_population["201
2 rides per person"],
         color = 'yellow', linewidth = 3, label = "2012")
ax1.plot(transit_type_over_population.index, transit_type_over_population["201
3 rides per person"],
         color = 'purple', linewidth = 3, label = "2013")
ax1.plot(transit_type_over_population.index, transit_type_over_population["201
4 rides per person"],
         color = 'pink', linewidth = 3, label = "2014")
ax1.plot(transit_type_over_population.index, transit_type_over_population["201
5 rides per person"],
         color = 'orange', linewidth = 3, label = "2015")
ax1.plot(transit_type_over_population.index, transit_type_over_population["201
6 rides per person"],
         color = 'black', linewidth = 3, label = "2016")
ax1.plot(transit_type_over_population.index, transit_type_over_population["201
7 rides per person"],
         color = 'grey', linewidth = 3, label = "2017")

ax1.set_title("Rides per Person per Year", fontsize = 20)
ax1.title.set_position([.5, 1])

ax1.set_xlabel("Ride Type", fontsize = 15)
ax1.set_ylabel("Rides per person", fontsize = 15)

ax1.legend()

plt.show()
```



We can see that ridership per person appears to be constant over the years. Since these methods of transportation go in and out of the city and into the suburbs, it appears that maybe migration to the suburbs over the years hasn't affected public transport use.

Ridership and Weather

Moving on from the effects of Uber and population, I was also interested in seeing how the weather, or more specifically, the amount of precipitation and snowfall, affects ridership.

In [397]:

```
#read in the weather file
fileWeather = "https://raw.githubusercontent.com/toddwschneider/nyc-taxi-data/master/data/central_park_weather.csv"
weather = pd.read_csv(fileWeather)
weather.head()
```

Out[397]:

	STATION	NAME	DATE	AWND	PRCP	SNOW	SNWD	TMAX	TMIN
0	USW00094728	NY CITY CENTRAL PARK, NY US	2009-01-01	11.18	0.0	0.0	0.0	26	15
1	USW00094728	NY CITY CENTRAL PARK, NY US	2009-01-02	6.26	0.0	0.0	0.0	34	23
2	USW00094728	NY CITY CENTRAL PARK, NY US	2009-01-03	10.07	0.0	0.0	0.0	38	29
3	USW00094728	NY CITY CENTRAL PARK, NY US	2009-01-04	7.61	0.0	0.0	0.0	42	25
4	USW00094728	NY CITY CENTRAL PARK, NY US	2009-01-05	6.93	0.0	0.0	0.0	43	38

In [398]:

```
#define a function that takes the dates and splits each date into quarters of the respective years
def split_by_quarter(date):
    split_date = date.split('-')
    q = int(split_date[1])
    if q <= 3:
        q = 1
    elif q > 3 and q <= 6:
        q = 2
    elif q > 6 and q <= 9:
        q = 3
    else:
        q = 4
    return split_date[0] + ' Q' + str(q)
```

In [403]:
```
#rename each column
rain_snow = pd.DataFrame({'Date': weather['DATE'], 'Precipitation': weather['P
RCP'], 'Snowfall': weather['SNOW']})

#apply method to split dates into quarters and clean up dataset
rain_snow['Quarter'] = rain_snow['Date'].apply(split_by_quarter)
rain_snow_by_quarter = rain_snow.drop(['Date'], axis=1)
rain_snow_by_quarter = rain_snow_by_quarter.groupby(['Quarter']).sum()

rain_snow_by_quarter.head()
```

Out[403]:

	Precipitation	Snowfall
Quarter		
2009 Q1	5.66	21.6
2009 Q2	19.91	0.0
2009 Q3	13.59	0.0
2009 Q4	14.46	12.4
2010 Q1	19.46	39.0

In [404]:
```
#dataframe that groups each type of transportation by quarter to combine with
 weather dataframe
transit_type_by_quarter = transit_data[transit_data.columns[:41]].groupby(["Tr
ansport Type (Broad)"]).sum().T
transit_type_by_quarter = transit_type_by_quarter.rename_axis("Quarter")
transit_type_by_quarter.head()
```

Out[404]:

Transport Type (Broad)	Airport Rail	Grand Total	MTA Rail	NJ Rail	NYC Buses	PATH	Suburban Buses
Quarter							
2008 Q1	48104.66	9875354.00	11456884.67	681900.0	5492012.67	492174.67	1579631.33
2008 Q2	56680.66	10296357.00	11891044.66	714000.0	5713352.01	513818.66	1703818.00
2008 Q3	40455.58	10048283.64	11639245.34	729000.0	5450016.56	514926.00	1722923.82
2008 Q4	37384.00	10093604.73	11707228.66	717600.0	5577832.59	500692.66	1646471.55
2009 Q1	30646.00	9730696.96	11247876.00	658700.0	5509373.84	485107.34	1529690.75

In [405]:
```
#combine ridership dataframe and weather dataframe by quarter
transit_type_and_weather = transit_type_by_quarter.join(rain_snow_by_quarter,
on='Quarter').dropna()
transit_type_and_weather.head()
```

Out[405]:

Quarter	Airport Rail	Grand Total	MTA Rail	NJ Rail	NYC Buses	PATH	Suburban Buses	Precip
2009 Q1	30646.00	9730696.96	11247876.00	658700.0	5509373.84	485107.34	1529690.75	
2009 Q2	35293.33	9899361.72	11438290.66	672200.0	5561328.26	488569.34	1603041.85	
2009 Q3	36051.34	9509110.65	11029056.00	684900.0	5138566.64	485881.34	1643765.99	
2009 Q4	37195.34	9947099.22	11549180.17	690800.0	5493322.49	488533.34	1643772.92	
2010 Q1	34375.62	9531632.29	11140003.33	659700.0	5216951.18	472845.34	1539389.11	

In [461]:
```
precipMin = transit_type_and_weather["Precipitation"].min()
precipMax = transit_type_and_weather["Precipitation"].max()
precip25th = np.percentile(transit_type_and_weather["Precipitation"], 25)
precip50th = np.percentile(transit_type_and_weather["Precipitation"], 50)
precip75th = np.percentile(transit_type_and_weather["Precipitation"], 75)
```

First, since airport rail ridership seems to be the most volatile, I want to see how this category's ridership has been affected by the amount of precipitation.

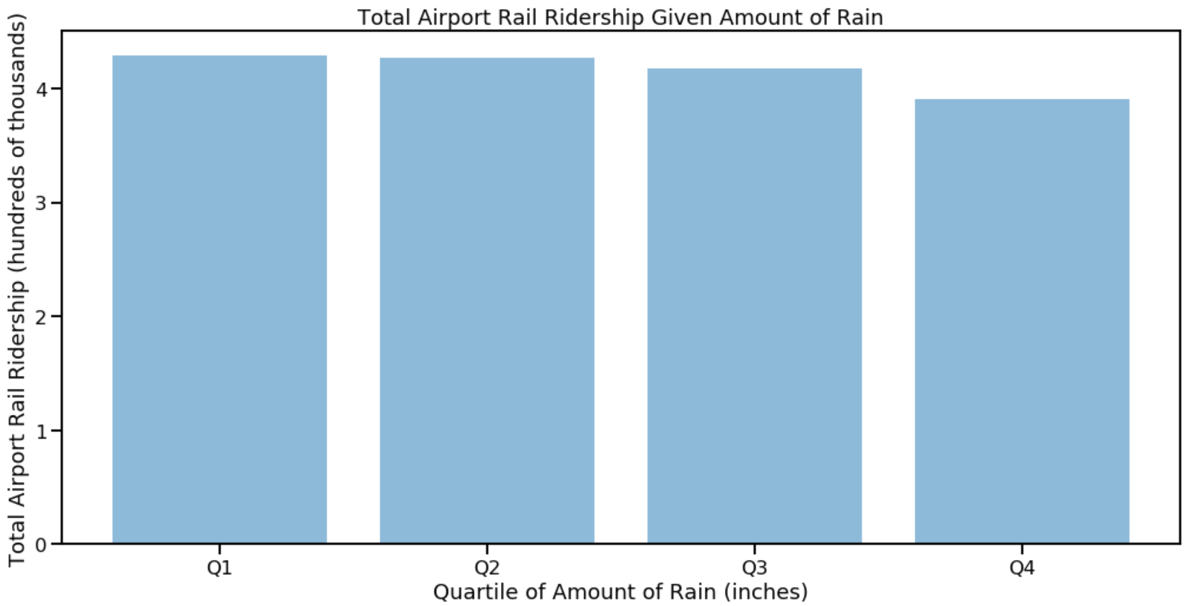
In [468]:

```
MTA1 = 0
MTA2 = 0
MTA3 = 0
MTA4 = 0

i = 0
while i < len(transit_type_and_weather["Precipitation"]):
    if transit_type_and_weather["Precipitation"][i] <= precip25th:
        MTA1 = MTA1 + transit_type_and_weather["Airport Rail"][i]
    elif transit_type_and_weather["Precipitation"][i] > precip25th and transit
_type_and_weather["Precipitation"][i] <= precip50th:
        MTA2 = MTA2 + transit_type_and_weather["Airport Rail"][i]
    elif transit_type_and_weather["Precipitation"][i] > precip50th and transit
_type_and_weather["Precipitation"][i] <= precip75th:
        MTA3 = MTA3 + transit_type_and_weather["Airport Rail"][i]
    else:
        MTA4 = MTA4 + transit_type_and_weather["Airport Rail"][i]
    i = i+1

mtadf = pd.Series([MTA1, MTA2, MTA3, MTA4], index = ['Q1', 'Q2',
                                                    'Q3', 'Q4'])
mtadf = mtadf.to_frame()

mtadf
```

Out[468]:

	0
Q1	429050.19
Q2	427292.30
Q3	417855.37
Q4	390766.59

In [476]:
```
plt.figure(figsize=(17,8))
plt.bar(mtadf.index, mtadf[0] / 100000, align='center', alpha=0.5)
y_pos = np.arange(len(mtadf.index))
plt.xticks(y_pos, mtadf.index)
plt.ylabel('Total Airport Rail Ridership (hundreds of thousands)')
plt.xlabel('Quartile of Amount of Rain (inches)')
plt.title('Total Airport Rail Ridership Given Amount of Rain')

plt.show()
```



It appears that airport ridership does seem to decrease with more rain. It would be interesting to see how all the transportation types are affected with both rain and snow.

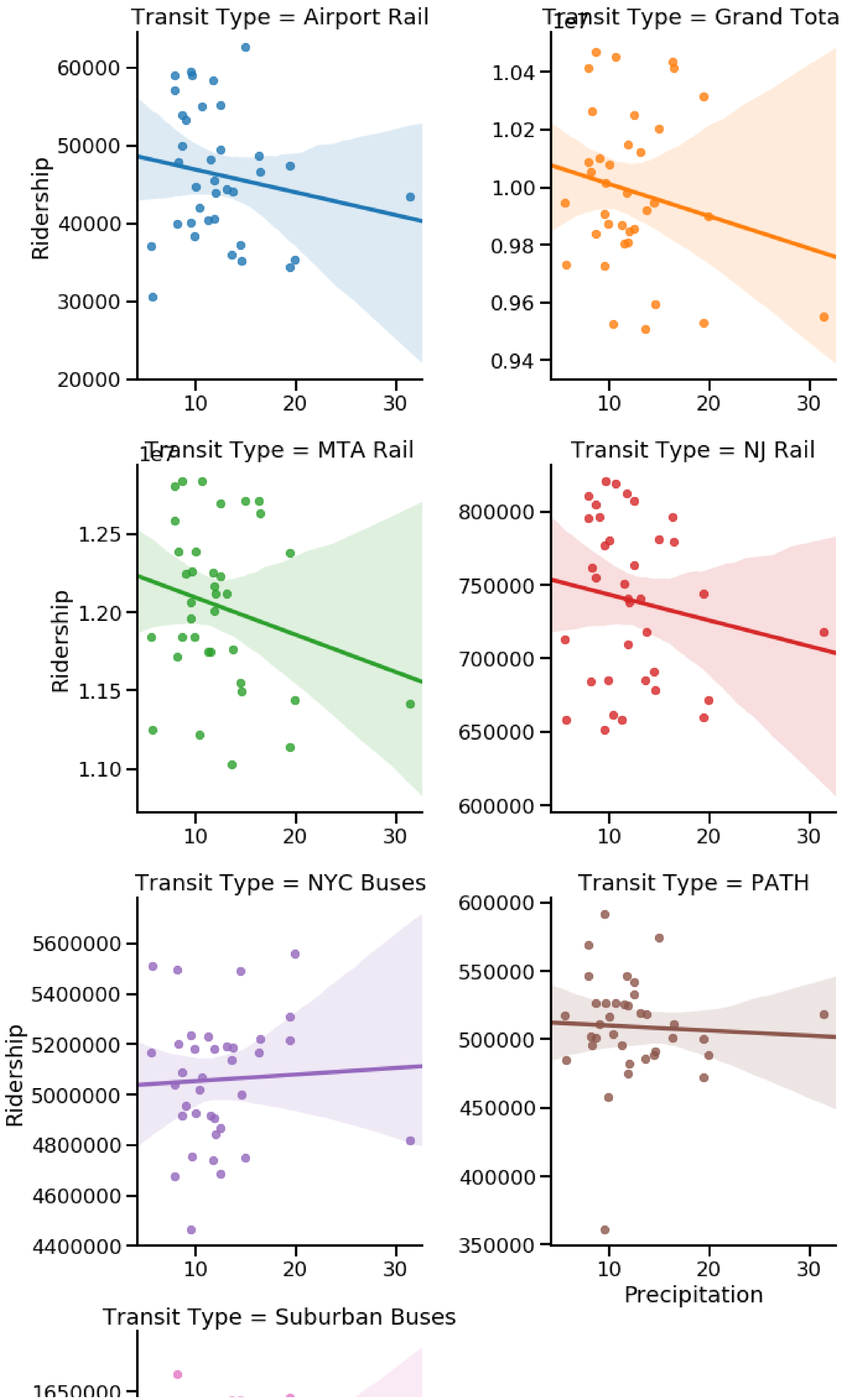
A bar graph isn't very telling of significance; let's look at some regressions.

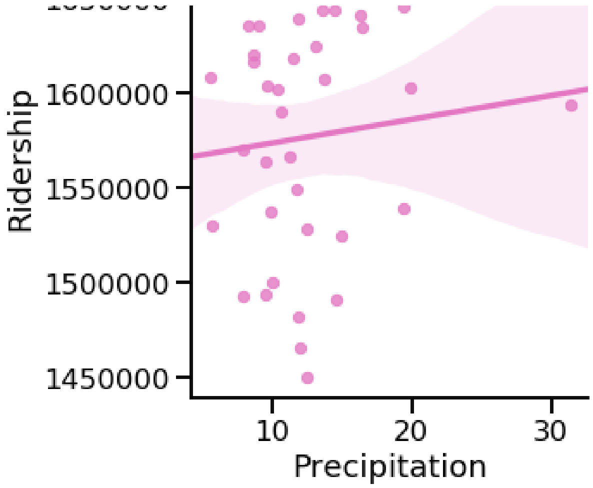
In [481]:
```
# iterate through each column excluding precipitation and snowfall
# assign value to transit type col according to each ridership value
# alongside preciptation and snowfall for that quarter
types = transit_type_and_weather.columns.tolist()
expanded_transit_type = pd.DataFrame()
for i in np.arange(len(types) - 2):
    values = transit_type_and_weather[types[i]].values
    precip = transit_type_and_weather[types[len(types) - 2]].values
    snow = transit_type_and_weather[types[len(types) - 1]].values
    # iterate through each quarter for each transit type
    for j in np.arange(len(values)):
        temp = pd.DataFrame({'Transit Type': [types[i]], 'Ridership': [values[
j]], 'Precipitation': [precip[j]], 'Snowfall': [snow[j]]})
        expanded_transit_type = expanded_transit_type.append(temp, ignore_inde
x=True)
expanded_transit_type.head()
```

Out[481]:

	Transit Type	Ridership	Precipitation	Snowfall
0	Airport Rail	30646.00	5.66	21.6
1	Airport Rail	35293.33	19.91	0.0
2	Airport Rail	36051.34	13.59	0.0
3	Airport Rail	37195.34	14.46	12.4
4	Airport Rail	34375.62	19.46	39.0

In [497]:
```
sns.lmplot(
    x="Precipitation",
    y="Ridership",
    data=expanded_transit_type,
    hue='Transit Type',
    col='Transit Type',
    col_wrap=2,
    scatter_kws={'s':40},
    sharex=False,
    sharey=False
);
```


Transit Type = Airport Rail
Transit Type = Grand Total
1e7
Transit Type = MTA Rail
1e7
Transit Type = NJ Rail
Transit Type = NYC Buses
Transit Type = PATH
Transit Type = Suburban Buses
Ridership
Precipitation
60000
50000
40000
30000
20000
1.04
1.02
1.00
0.98
0.96
0.94
1.25
1.20
1.15
1.10
800000
750000
700000
650000
600000
5600000
5400000
5200000
5000000
4800000
4600000
4400000
550000
500000
450000
400000
350000
1650000
10
20
30



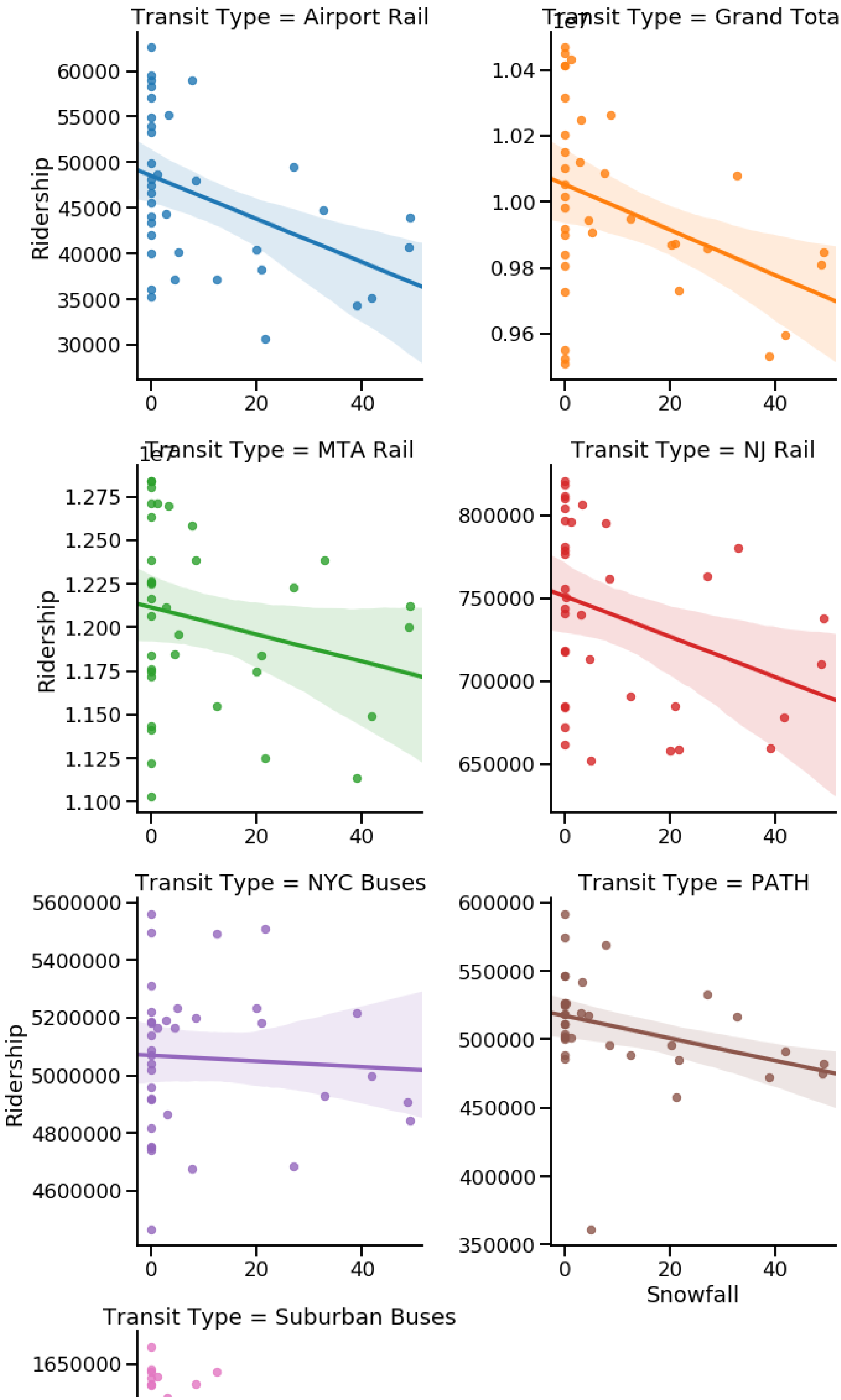
These are graphs of how ridership is affected by rainfall. In general, transportation seems to decrease with increased rain; however, there are some exceptions, including both buses and the PATH.

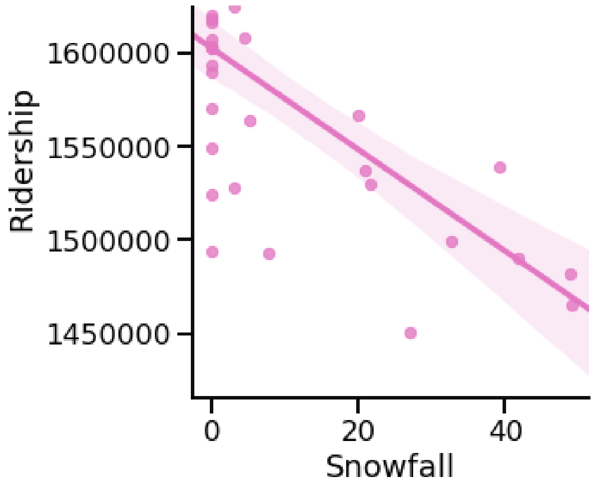
But in general, we see that the Grand Total decreases with an increase in rainfall, suggesting public transportation use goes down with more rain (although this may be heavily influenced by MTA rail, which has the highest use).

In addition, the shaded region indicates confidence interval. We see that the confidence interval is very wide especially as the amount of rainfall increases, so this conclusion must not be taken as fact.

Now, let's look at snowfall.

In [483]:
```
sns.lmplot(
    x="Snowfall",
    y="Ridership",
    data=expanded_transit_type,
    hue='Transit Type',
    col='Transit Type',
    col_wrap=2,
    scatter_kws={'s':40},
    sharex=False,
    sharey=False,
    x_jitter=.1
);
```


Transit Type = Airport Rail
60000
55000
50000
45000
40000
35000
30000
Ridership
0
20
40
Transit Type = Grand Total
1e7
1.04
1.02
1.00
0.98
0.96
0
20
40
Transit Type = MTA Rail
1e7
1.275
1.250
1.225
1.200
1.175
1.150
1.125
1.100
Ridership
0
20
40
Transit Type = NJ Rail
800000
750000
700000
650000
0
20
40
Transit Type = NYC Buses
5600000
5400000
5200000
5000000
4800000
4600000
Ridership
0
20
40
Transit Type = PATH
600000
550000
500000
450000
400000
350000
0
20
40
Snowfall
Transit Type = Suburban Buses
1650000



Here, we see that snow seems to affect transit more than rain. All the categories of transportation have downwards sloping regression lines, and the confidence intervals are significantly narrower. This seems to confirm what we already know: snowfall means we do not want to get out of the house, let alone take public transportation.

Conclusion

This project set out to answer the question: What effects ridership of NYC Public Transportation?

We looked at Uber, population, and weather.

Becuase Uber does not release any large amounts of their data on ridership, it is hard to draw conclusions on what happened to public transportation based on just their date of entrance.

We then looked at population. It seems that all the transportation types are affected by population changes equally over the years.

Finally, we looked at weather data. This is where we could really draw some conclusions. We saw that both rainfall and snowfall affects ridership, but snowfall more so, as there are strong correlations between the amount of snow and decrease in ridership across all the transportation categories. This is likely because of the presence of snow days, which means public transportation also shuts down.